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ABSTRACT

A path modeling approach is adopted to examine inter-relationships between factors influencing computing behavior and computing course performance. Factors considered are gender, personality, intellect and computing attitudes, ownership and experience. Among many other conclusions, intrinsic motivation is suggested as a major factor which can explain many variables' relationship with course performance. Similarly to the common finding for non-computing specialist students, a male advantage in previous computing experience is observed, gender differences in computer ownership partially explaining this. In the absence of an attitudinal gender difference, the ownership difference is suggested to stem from the perception of computers as objects stereotypically bought by and for males. However, while having implications with respect to the gender imbalance usually observed on programming-oriented and more technically-oriented applications courses, these differences are not shown to confer a male advantage in course performance.

INTRODUCTION

Although commonplace, multivariate studies of factors related to computing course performance have tended to adopt a largely atheoretical perspective, explanations for relationships often remaining unclear [e.g. 1, 2, 3, 4]. This results from the studies' agenda of identifying variables useful in predicting success in introductory computing courses, with a view to indirectly aiding the identification of students with a good chance of success in subsequent computing majors. There is therefore a shortage of work on computing-specialist students and of theoretically-oriented literature exploring the structure of predictor variables' inter-relationships and these variables' relationships with computing course performance.

The present work sought to build and test a theoretically coherent path model[1] describing the structure of relationships among variables influential in determining the performance of students on a programming-oriented computing course. Particular attention was paid to the role which the stable or relatively stable individual difference factors of gender, personality and intellect have in influencing computing attitudes and behaviors, and the implications of such influences for performance. Consideration of these connections is important in understanding why certain variables predict performance, with the goal of identifying key unifying concepts responsible for predictivity. Quite apart from its importance in advancing theoretical understanding, from a practical perspective, the identification of such concepts is useful for counseling purposes and in developing a minimal set of selection criteria which can yield maximal predictive utility. Also, and equally important, this type of study can be informative on the issue of redressing the gender imbalances, favoring males, almost always observed on technical computing courses and in industrial and commercial technical computing posts. It is with this topic that we commence.

Previous work seeking to explain the above gender imbalances concentrates almost entirely on schoolchildren or members of non-specialist introductory computing courses. Such work has often shown lesser female computing experience

[1]Although path modeling assumes the existence of specific causal relationships, the acceptance of a model does not prove the veracity of such causal assumptions. Hence, though causal terminology is sometimes used in the present paper, no claim as to proof of causality is made.

[e.g. 5, 6, 7, 8] and less positive female attitudes towards computing [e.g. 9, 10, 11]. Computer dependency has also been cited as a largely male phenomenon [12]. Explanations of these observations include lack of female confidence resulting from male monopolization of computing resources at school [13, 14, 15], lack of female role models and transfer of female mathematics anxiety to the computing domain [6], and lesser encouragement of female computing activity [e.g. 6, 8, 16]. These factors have also been cited in connection with lesser female computer ownership [e.g. 11, 14, 16, 17], lesser female computer game playing [14, 18, 19] and perceived lesser vocational relevance of computers on the part of females [e.g. 14, 20].

Based on the previous literature then, the present theoretical model assumed that social stereotyping of computing as a male activity results in less positive female computing attitudes in terms of computer engagement (a behavioral construct indicating a high degree of computing activity, but, in the present context at least, involving no negative consequences). The model depicted this greater male engagement as leading to greater male accumulation of computing experience both directly (e.g. greater engagement should lead to greater male utilization of computing resources in schools, colleges and places of work) and indirectly via computer ownership (greater male computer engagement leading to a greater likelihood of male computer ownership, in turn resulting in greater male accumulation of computing experience). Given that the present focus was on computing specialists, and that therefore the approach to computing of the present females might be gender atypical, whether the attitudinal, ownership and experiential gender differences found in the non-specialist literature would be present was one of the most interesting aspects of the study. This was particularly so given evidence that females often enroll in computing courses for pragmatic reasons associated with enhancing employment prospects [5], thus implying that the present females may not be gender atypical in their computing attitudes and behavior.

Gender differences in personality might be added to social reasons as a partial explanation of gender differences in computer engagement. In particular, the emotional sensitivity - tough-poise continuum is relevant here. Relative to emotionally sensitive people, those high in tough-poise lack sensitivity, focus upon facts rather than feelings, and are quicker to adopt definite positions on issues, paying little attention to subtleties [21]. Such differences have been linked to a bias towards arts (emotional sensitivity) or sciences (tough-poise) [22]. Additionally, males and females are often considered as falling towards the higher and lower ends of this continuum respectively [23, 24]. So, granted that programming is clustered with sciences in terms of its perceived attributes [25], that computer science students' vocational interests are similar to those of science and engineering students [26], and that science attitudes are positively related to computer attitudes [18, 27], the present theoretical model included an indirect path linking gender and computer engagement by way of differences in tough-poise. The existence or otherwise of a bivariate gender – tough poise relationship bore upon the issue of whether females opting to specialize in programming-oriented computing exhibit more masculine personality characteristics than females generally.

To the extent that males were hypothesized to be more highly computer engaged than females, this predicted a male advantage in course performance as a result of greater intrinsic motivation, the model representing engagement as having a direct positive influence upon course performance. Although it is possible that extreme computer involvement can have negative effects upon working performance (see various anecdotal accounts [e.g. 28, 29]), or, more relevantly here, academic performance [12], high computer engagement was seen in the present work as indicating the presence of a positive motivating force having positive effects upon academic performance. This was the case if only because the present students were studying computing, rather than other academic subjects where high computer engagement might be a distraction.

A second personality dimension which can be adduced as a possible causal influence in the development of high computer engagement is introversion – extraversion. Here, self-reports of computer dependent individuals indicate a lack of sociability, and a greater concern with objects than people. Rather than this arising from dependency, Shotton [12] portrayed this orientation as resulting from lack of parental closeness and warmth during childhood, viewing dependency as a strategy for coping with life adopted by introverted individuals. Hence, dependents were said to see computers as offering many of the benefits of social interaction without any of the drawbacks. The more anecdotal literature has also painted highly computer involved individuals as lacking sociability [e.g. 30, 31]. From this, the present theoretical model depicted decreasing extraversion (increasing introversion) as leading to increasing computer engagement and subsequently computer ownership.

Shotton's dependents were characterized as schizoid personalities. Though often used in connection with clinical disorders nowadays [32], the term schizoid also describes solitary individuals who tend to divorce emotional from intellectual considerations. It is this second usage which is adopted here, and note then that both high tough-poise and introversion are constituents of the schizoid typology. The introverted, non-emotional nature of schizoids leads them to concentrate much energy upon intellectual matters and to attach importance to intellectual prowess [12, 33]. Other things being equal (such as fluid, i.e. innate, intelligence), we would therefore expect better performance upon psychometric measures of intellect on the part of schizoid personalities. This follows because the energy invested in intellectual matters over an extended period of time should sharpen schizoids' reasoning skills and because of higher schizoid test- taking motivation. Such reasoning led to hypotheses directly linking both greater introversion and greater tough-poise with better intellectual performance. Subsequently, in that measured intellectual level should obviously be positively associated with educational attainment (both because of true differences in intelligence and the above performance reasons), the model also contained a direct positive link between intellectual performance and course performance. This link was consistent with studies of students on non-specialist computing courses [e.g. 2, 34, 35]. The foregoing hypotheses implied a negative indirect effect of extraversion upon course performance via intellectual performance, and a positive indirect effect of tough-poise upon course performance via intellectual performance, thereby testing the proposition that the greater motivation and intellectual acuity of schizoid individuals would lead to better course performance. The hypothesis relating to the former of these two effects was consonant with observations of better introvert intelligence test performance for teenage schoolchildren and university students [36] and of better introvert educational performance in the general educational literature [37, 38].

As well as having negative indirect effects via intellectual performance, extraversion was represented as having a negative effect upon course performance more directly. The rationale here stemmed from Eysenck's neurophysiological model of introversion – extraversion [39], which explains introvert – extravert differences in terms of the latter requiring greater environmental stimulation to reach an optimal level of cortical arousal than the former. Thus, from a behavioral perspective, extraverts are said to be likely to neglect their academic studies in favor of (more stimulating) social activities [40, 41]. At the same time, and at a cognitive level, extraverts often perform non-optimally because of under-arousal in the non-stimulating situations typical of academic study. Also, extraverts are more adept at processing rapidly presented information, while introverts perform better on tasks with slower information processing demands and at tasks requiring reflectiveness: academic work in general, and computing work such as programming and systems analysis in particular, is of this nature [42]. Support for such reasoning in the literature on non-specialist computing students is equivocal. For example, as would be predicted, negative relationships have been identified between scores on the Active, Vigorous, Impulsive, Dominant and Sociable scales of the Thurstone Temperament Schedule and introductory computing course performance [2]. But other work has failed to identify better introvert performance in introductory computing courses [43, 44], possibly because of methodological factors [44, 45]. Given the theoretical rationale, the present hypotheses concerning negative direct and indirect links between extraversion and course performance were forwarded despite this confusion in the computing literature.

Having considered gender, attitudinal, intellectual and personality issues, a final factor considered in the model was computing experience, with the expectation that increasingly greater experience would lead directly to better computing course performance because of the declarative and procedural knowledge which it furnishes. Previous findings for students taking both rudimentary courses [7, 46] and non-rudimentary courses [47, 48] confirm the intuition that a positive relationship between experience and computing course performance should exist. Also, by definition, a major determinant of an individual's computing experience is the extent to which they are computer engaged: to some extent, people compute (and therefore build-up experience) because they are drawn towards computers, and a direct path expressing this was also included in the model. Finally, note that the two aforementioned hypotheses implied an indirect relationship between computer engagement and course performance via experience.

The hypotheses developed in the preceding pages are represented in the theoretical path model presented as Figure 1. The aim of the present study was to assess the accuracy of this model in the light of data for students specializing in programming-oriented computing and to consider the ensuing theoretical and practical implications.

------- INSERT FIGURE 1 HERE -------

METHOD

Design

The study was of a correlational nature, adopting a path modeling approach involving the eight variables depicted in Figure 1.

Participants

Participants were students studying full-time for the Higher National Diploma (HND) in Computing at Bolton Institute (HNDs are vocationally-oriented subdegree qualifications available in the UK.). The Computing course is taken by aspiring programmers and systems analysts.

Participation in the study was encouraged but voluntary. Complete data sets were obtained for 86 students (74 males and 12 females) in the age range 18 to 47 (mean age=22.08 years, SD.= 5.94 years). This represented 50.89% of students enrolling. Students yielding full data sets were representative of the students as a whole in terms of both gender and age.

Materials

The British edition of the Computer Programmer Aptitude Battery (CPAB) was used to measure intellectual performance. This consists of five time-limited tests, each adopting a multiple choice format. The Verbal Meaning test is said to measure communication skill, the Reasoning test to measure ‘ability to translate ideas and operations from word problems into mathematical notations’, the Letter Series test to measure ‘abstract reasoning ability’, the Number Ability test to measure ‘ability to quickly estimate reasonable answers to computations’, and the Diagramming test to measure ‘ability to analyze a problem and order the steps for solution in a logical sequence’ (all quotations from the Examiner's Manual [49]). Scores for these subtests were summated to give an overall measure of intellectual performance. Because of the distinction between performance and intelligence / aptitude mentioned elsewhere, in spite of the battery used, the term intellectual performance was preferred to ‘programming aptitude’ in naming the CPAB variable.

Form A of the Sixteen Personality Factor Questionnaire (16PF – [50]) measured personality. Low and high scores on each dimension indicate tendencies towards the first and second mentioned ends of the continua respectively. Scores on the second-order introversion - extraversion factor were calculated using Krug and Johns’ [51] equation for combined genders. However, since the aforementioned authors presented no combined gender equation for emotional sensitivity - tough-poise, the earlier equation of Cattell, Eber and Tatsuoka [50] was used to calculate this index. Both equations assumed Sten score data and therefore data was converted to Sten scores using Sten score equivalents for undifferentiated British undergraduates [52].

Information on age, gender, ownership of a computer (yes/no) and computing experience was obtained using a biographical questionnaire. Questions relating to previous computing experience were partially derived from previous research on computing experience [9, 53]. Data relating to number of word processing packages previously used, number of database packages previously used, number of spreadsheet packages previously used, number of miscellaneous applications packages previously used, number of high-level programming languages previously used and number of low-level programming languages previously used were subjected to Principal Axis Factoring. This analysis yielded a single factor, indicating the presence of a general experiential factor. Factor scores relating to this factor were used as experiential data.

Computer engagement was measured by the Apathy – Engagement subscale of the Computer Apathy and Anxiety Scale (CAAS – [54]). This instrument consists of a number of opinion statements requiring agreement / disagreement using a five-point Likert-type response format.

Finally, course performance was measured in terms of average performance during the course, this taking into account both coursework gradings (70%) and examination gradings (30%).

Procedure

Students sat the CPAB during induction week. Attempts were made to increase motivation by stressing the CPAB's relevance, students being informed that employers often use the instrument in selection of computing staff. Subsequent to this, the battery was administered in accordance with standardized instructions laid down in the manual. Students were either asked to complete the CAAS and biographical questionnaire at the end of the CPAB testing session or were mailed the questionnaires a few weeks before the start of term.

For some students, 16PF administration had to be delayed until the final week of the course's first term. This was not a problem inasmuch as psychometric personality approaches assume personality to be reasonably stable [24].

Prior to administration, as with the CPAB, the 16PF's use in employment selection procedures was emphasized in an attempt to relate the instrument to students' circumstances. Subsequently, students were asked to read the instructions in the 16PF question booklet before filling in the response sheet.

Course performance data was obtained from tutors at the end of the course.

RESULTS

Path analysis was conducted using EQS [65]. As is often the case, a significant chi-square statistic (χ^2=32.60, *df* =15, *p*=0.005) and a low Comparative Fit Index (CFI=0.78) revealed that the theoretical path model inadequately reflected the input covariance matrix describing relationships between variables in the model (see Table 1 for the corresponding correlation matrix).

------- INSERT TABLE 1 HERE -------

The theoretical model was modified by freeing and then adding constraints according to results of Lagrange Multiplier and Wald tests respectively [56].

Lagrange multiplier statistics for the run testing the theoretical model and a second run, in turn, suggested the addition of direct paths linking gender and computer ownership (indicating greater male ownership) and gender and intellectual performance (males performing better). Examination of fit statistics confirmed that addition of each of these links considerably improved the model's fit to the data.

After adding the above two links, Wald tests resulting from repeated runs suggested the presence of six redundant direct links. However, in the event, only the first four of these links were removed (direct paths between extraversion and engagement, experience and course performance, tough-poise and engagement, and extraversion and course performance). The Wald tests' suggestions of the removal of direct paths connecting gender and engagement and engagement and ownership were not acted upon, since, though these links' path coefficients were non-significant, their deletion resulted in a marked decrease in CFI (CFI is preferred to chi-square, and Bentler-Bonett normed and non-normed fit indices for models based upon small sample sizes – [55, 56]).

The above process gave a non-significant chi-square value of 18.28 (df =17, p=0.371), signifying a good fit between model and data. This was confirmed by a CFI of 0.98: a value greater than the 0.90 acceptable as a minimum [56].

The partially data driven nature of the modified model (see Figure 2) demanded some assessment of its validity. Here, correlation of parameter estimates present in both the original and modified models revealed a high degree of correspondence (Pearson's r =0.99, df =15, p<.0005 – one-tailed). This showed that relationships expressed in the modified model constituted a good reflection of those in the original model, despite the *post hoc* alterations made [56].

While derived by maximum likelihood methods, the path coefficients reported can be considered identical to ordinary least squares regression beta coefficients. In the following verbal summary, all Pearson's r coefficients are evaluated at 84 df for one-tailed hypotheses.

------- INSERT FIGURE 2 HERE -------

Starting with gender differences, the observed correlation matrix revealed significantly greater male tough-poise as hypothesized (r =.27, p<.05 – with males coded higher on the gender variable). Because gender was the only variable logically prior to tough-poise, this relationship was modeled as a simple bivariate relationship and the direct link in the model corresponded to the above Pearson's *r* (p21=.27, $p<.05$), resulting in explanation of around 7% of the variance in tough-poise (df =1,84, $p<.05$).

Contrary to hypothesis, male computer engagement was not significantly greater than that of females (r =.16, $p>.05$). However, though the link was non-significant, retention of the direct gender – engagement path hypothesized in the theoretical model (p51=.16, $p>.05$) made a substantial contribution to the fit between the modified model and the data. But the small magnitude of this link meant that only a very small portion of the correctly hypothesized greater male computer ownership (r =.37, $p<.0005$) was attributable to gender differences in engagement (p51p65=.03). Rather, a non-hypothesized direct gender - ownership link (p61=.34, $p<.0005$) explained the bulk of the relationship between these two variables. Together, gender and engagement explained roughly 17% of computer ownership's variance (df =2,83, p=.0005).

Further to the above, the hypothesized male advantage in computer experience was observed (r =.29, $p<.01$), but the notion that this would largely be attributable to gender differences in computer engagement causing gender differences in computer ownership, and therefore experience, went unsupported, this effect being negligible. Nearly half the magnitude of the gender - experience relationship was explained by the indirect gender - ownership - experience path (p61p76=.12), ownership having a strong relationship with experience as hypothesized (r =.40, $p<.0005$ and p76=.34, $p<.01$). The remainder of the gender - experience relationship went unexplained. Although computer engagement was represented as influencing experience via computer ownership, this hypothesized indirect effect was rather small (p65p76=.06), the engagement – ownership component of this compound path not reaching significance (p65=.18, p>.05). Nevertheless, engagement was positively related to experience (r =.31, p<.01), and this was reflected in a direct link in the model as also hypothesized (p75=.23, p<.01). In total, engagement and ownership accounted for approximately 21% of the variance in experience (df =2,83, p=.0001).

Both extraversion (r = -.32, p<.01) and tough-poise (r =.26, p<.01) exhibited bivariate relationships with intellectual performance and, as hypothesized, the model contained direct links showing increases in intellectual performance with both decreasing extraversion (p43= -.34, p<.001) and increasing tough-poise (p42=.25, p<.05). Also, in one of the modified model's two non-hypothesized links, male intellectual performance was depicted as exceeding that of females (p41=.22, p<.05), this reflecting the significant bivariate relationship (r =.31, p<.01). Around 24% of intellectual performance's variability was attributable to the above three variables combined (df =3,82, p<.0001).

In contrast to their roles in explaining intellectual performance, the two personality variables were not related to computer engagement: contrary to hypotheses, null bivariate correlations showed that lesser extraversion (or increasing introversion) and tough-poise did not make for greater engagement (r = -.04, p>.05 and r = -.03, p>.05 respectively). Consequently, the previously mentioned (non-significant) effect of gender upon engagement (p51=.16, p>.05) constituted the only direct effect on the latter variable, limiting the predicted variance in engagement to a non-significant 3% (df =1,84, p>.05).

Finally, bivariate relationships existed between course performance and all variables hypothesized to have direct effects upon it: r = -.22 (p<.05) for extraversion, r =.42 (p<.0005) for intellectual performance, r =.24 (p<.05) for engagement and r

=.21 (p<.05) for experience. On the other hand, only intellectual performance (p84=.43, p<.01) and engagement (p85=.25, p<.01) had direct links in the modified model. Despite this latter link, there was minimal support for the hypothesized male advantage in course performance via computer engagement (p51p85=.04), owing to the non-significant gender – engagement effect. A large proportion of the negative extraversion - course performance relationship was explained by an indirect effect via intellectual performance (p43p84= -.15), while a precursory (or 'spurious') effect arising from engagement's direct links with both experience and course performance (p75p85=.06) and a number of smaller spurious effects were enough to explain the absence of a direct link between experience and course performance. By virtue of the two direct links present, around 26% of the variance in course performance was explained (df =2,83, p<.0001).

DISCUSSION

In considering the implications of the present research, the discussion is structured around the themes of gender, personality and course performance.

As is usually the case for programming-oriented courses, males greatly outnumbered females (by a ratio of seven to one). Towards the end of remedying such imbalances, it is useful to tease out possible explanations as to what enabled the present females to enroll in and persist with such a male dominated course.

Results supported the previous finding that the male advantage in computing experience commonly observed for students taking non-specialist computing courses [e.g. 6, 7, 8] sometimes generalizes to computing specialists [5]. Findings were also consistent with the non-computing specialist literature showing greater male computer ownership [e.g. 11, 14, 16]. However, the merely marginal greater male computer engagement which existed proved insufficient to explain the male ownership and experiential advantages. Also then, the compound hypothesis of greater male engagement leading to greater male computer ownership and subsequently to greater computing experience went unsupported. The same was also true for the hypothesis that there would be a male advantage in course performance by virtue of the greater intrinsic motivation which higher male computer engagement would have signaled. The observation of only a slight (non-significant) gender difference in computer engagement contrasts with the more markedly positive male attitudes often found for non-computing specialists [e.g. 9, 10, 11].

The failure of gender differences in engagement to explain greater male computing experience suggests that, even where females are not averse to engaging in computing activities, social factors may limit such activities. One way in which such factors seem to act is via gender differences in computer purchasing. Here, the non-hypothesized direct link expressing greater male ownership (rather than an indirect gender – ownership link via engagement) indicates that factors such as gender stereotyping of computers as objects to be purchased by and for males, rather than gender differences in computing interest, can help to explain gender differences in computer ownership which occur even among students starting to specialize in computing.

Though computer ownership was depicted as directly influencing computing experience, and ownership differences played a part in explaining experiential gender differences, the above results are not as pessimistic for females as might be thought in that female ownership and experiential disadvantages did not produce a substantial female deficit in course performance (and neither did the non-hypothesized male advantage in intellectual performance which existed). It is possible though, to envisage how lesser female ownership and experience might make enrollment in programming-oriented courses appear a non-viable option to females less positively computer engaged than those presently considered.

The observation that gender differences in computer ownership can occur in the presence of minimal differences in computer engagement implies that at any particular time there is likely to be a body of non-computer owning females with reasonably strong positive attitudes to computers. The targeting of advertising at such females might be lucrative for computer manufacturers. Such a marketing strategy might de-emphasize issues which possibly reinforce female beliefs in computers as objects stereotypically owned by males (e.g. issues surrounding computing power, and graphics capabilities for game playing) and instead emphasize the machines' usefulness for general applications. This follows from research showing females as more likely than males to view computers as tools for performing tasks which are not intrinsically computer-centered [9]. As well as proving profitable for the computing industry, by increasing the number of female computer owners and thereby increasing the number of females with greater computing experience, such a strategy could only have positive benefits in reducing gender asymmetries in programming-oriented and more technically-oriented applications courses (although, as discussed subsequently, to have a major impact upon asymmetries in the former type of course, females would still need encouragement to engage in programming activities). On the other hand, the present negligible bivariate relationship between ownership and course performance indicates that greater computer ownership would not necessarily make for better female course performance. The extent to which this null relationship was attributable to previously non-computer-owning students purchasing a computer during the course or because college computing facilities were adequate for non-computer-owning students' needs is unclear. Whatever the case, although greater computer self-efficacy has been cited as a benefit of computer ownership [57], it seems that ownership at a course's outset does not necessarily translate into better course performance when students are computing specialists.

While supporting the general literature on gender differences [23, 24], the observation of greater male tough-poise was interesting in that, given their willingness to enter a male dominated domain, the present females might have been assumed to exhibit a more masculine position on the emotional sensitivity – tough-poise continuum than females in general. The evidence that this is not the case is reinforced by the observation that, though a subset of the present females exhibited greater computer engagement than a group of females taking a non-programming-oriented IT course with some technical components, the tough-poise of the two groups of females did not differ [33].

Overall, the present results suggest that non-stereotypically positive female computer attitudes, rather than possession of personality characteristics more stereotypical of males, had a bearing upon females' enrollment in the present course. It also seems that females displayed a real interest in the subject domain, and did not simply enroll out of pragmatism associated with enhancing employment prospects [5].

Further study is needed to determine why some females develop highly positive computer attitudes. In spite of the present conclusion that males enjoyed an advantage in computing experience generally, the study contrasting the present females with IT course females highlighted the importance of programming experience (but not applications experience) in explaining the present females' disposition towards enrolling in a programming-oriented course. Since gender differences in the extent to which males and females stereotype computing as a male activity have been identified in children as young as four years old [17], developmental studies, focussing on issues such as occupations, academic biases and pastimes of parents, could provide useful pointers as to why some females display greater computer engagement and acquire greater programming experience than other females. The observation that the present females had previously studied fewer arts subjects, but not more science subjects, than IT females [33], endorses the notion that an arts-oriented background biases some females against enrolling in programming-oriented courses.

Turning away from gender issues, along with the other schizoid personality dimension of introversion - extraversion, tough-poise exhibited a negligible bivariate relationship with computer engagement. This did not support anecdotal writings [30, 31] and non-psychometric empirical observation [12] concerning the personality characteristics of highly computer involved individuals. Another null finding was that involving the possibility of greater computer ownership among more introverted individuals because of greater computer engagement, the bivariate extraversion - ownership relationship approaching zero.

The above fails to sustain the idea that, because of the opportunities which computers present for non-social interaction, increasing introversion and tough-poise leads to increasing computer engagement, and consequently greater computer ownership, among programming-oriented students. Despite this, comparison of the present students (male and female combined) with IT students revealed the present students to display greater introversion but not tough-poise [33]. Thus, combined the studies show that although relatively highly computer engaged individuals tend towards introversion, within groups of such individuals there is no relationship between introversion and engagement. This raises the possibility of a threshold effect, whereby above a certain level of computer engagement a negative extraversion – engagement relationship disappears. Further investigation of the existence and possible causes of this effect would be useful, as would research into the causes of computer engagement more generally, in view of the small amount of variance presently explained. As previously recommended with respect to females, such research might concentrate on developmental issues surrounding art – science orientation, especially since, though excluded from modeling on the grounds of theoretical parsimony, a science attitude variable explained 14% of the variance in engagement. This confirms previous work showing science - computing attitude connections [18, 27].

While not related to computer engagement, both increasing tough-poise and introversion made for better intellectual performance. This favors the notion that students tending towards the schizoid personality type display sharper intellects because of long-term engagement in reflective intellectual activities and because their greater pride in intellectual skills results in higher motivation to perform well. Further, intellectual performance was positively related to course performance. Hence, the two hypothesized indirect effects of the schizoid personality factors upon course performance via intellectual performance were both present, the intellectual bent and greater motivation of the more schizoid individuals appearing to equip them better with respect to the course's demands. (However, there was a null bivariate tough-poise - course performance relationship: a number of small paths in a saturated model [not depicted] nullifying the indirect effect of tough-poise upon course performance via intellectual performance).

The bivariate relationship indicating superior course performance of relative introverts, reflected in the negative extraversion – intellectual performance – course performance path, was consistent with general research on the role of personality as a determinant of higher education performance [37, 38], and some of the literature on non-computing specialists [2]. But while greater introversion seemed to aid course performance, the hypothesized direct linkage was absent from the modified model. The lack of this direct linkage suggests that the oft found better educational performance of introverts from the teenage years onwards might be the product of a complex interplay between intellectual and motivational factors, rather than largely resulting from more extraverted students neglecting study in favor of more arousing pursuits as is sometimes mooted [40, 41]. With regard to this, it is important to appreciate the significance of the idea that the more schizoid individuals were partly hypothesized to exhibit better intellectual performance because of pride in their intellectual skills. This implies that students' perception of the importance of performing well in intelligence / aptitude tests is a salient factor in determining the magnitude of relationships between schizoid personality variables and performance on such tests. Specifically, if much hinges upon test performance (e.g. if it is part of a selection process or forms part of course assessment), then extrinsic motivation is likely to result in better test performance on the part of students with greater extraversion and lower tough-poise relative to voluntary testing situations where only intrinsic motivation is likely to be important. In this latter situation (which pertained here), students possessing more schizoid characteristics will still be motivated to perform well (because of pride in their intellect). For these reasons, it can be hypothesized that personality by situation interactions will lead to greater relationships between schizoid personality factors and intellectual test performance in the presence of only intrinsically motivating circumstances, and smaller relationships in the presence of both intrinsic and extrinsic motivational factors. (Only in the latter circumstances can we justifiably claim to measure the intellectual *capacity / aptitude* of non-schizoid individuals: in the former situation only the intellectual *performance* of such individuals is measured [36].)

The possible moderating effect of situational variables on the relationship between schizoid personality factors and intellectual test performance is important because lack of test-taking motivation on the part of some (less-schizoid) members of a cohort will influence the size of relationships between scores on intellectual measures and indices of educational outcomes. In particular, when intelligence test outcomes are important to all individuals (e.g. when tests are used for selection purposes etc.), the closer matching of motivational factors across the testing and the educational situation would be expected to lead to higher test – course performance correlations. However, despite the fact that such conditions were not presently met, both the bivariate and path modeling results warranted the conclusion that intellectual performance exceeded attitudinal, personality and experiential factors in the size of its relationship with course performance. The connection between intellectual performance and course performance was consistent with previous observations for both specialist and non-specialist students [2, 34, 47].

The relatively stable nature of personality traits means that some (more schizoid) students will tend to have an advantage over other (less schizoid) students simply because of their nature, the intrinsic motivation which causes the former students to perform well on tests also making them perform well on educational courses. In addition to this general intellectually rooted intrinsic motivation, a second type of intrinsic motivation more closely associated with computing can also be said to have been at work, this explaining the positive relationship between computer engagement and course performance. For example, if a student finds learning about a course's subject matter intrinsically rewarding, they will devote greater time to it, and will assimilate knowledge with less cognitive effort. Knowledge is even likely to be accumulated during leisure hours, computing activities probably occupying much of highly engaged students' spare time. Indeed, the intrinsic motivation associated with computer engagement and leading to greater computing experience probably constitutes one reason why the hypothesized direct connection between experience and course performance did not materialize, although, in common with previous research on specialists and non-specialist students [47, 7, 46], a bivariate relationship was observed. The modified model partially explained this in terms of computer engagement's positive relationships with both experience and course performance (the positive computer engagement - experience link adds to other studies showing attitude - experience relationships [e.g. 10, 58]). Thus, differences in computer engagement, and therefore intrinsic motivation, were represented as leading both to differences in computing experience and differences in course performance, and these differences were seen as partially responsible for the relationship between experience and computing course performance. However, bear in mind that the magnitude of the residual coefficient, expressible as a direct experience – performance link in a saturated model, was twice the size of the effect involving prior differences in engagement, and in other situations a direct effect might occur. Specifically, the course's relatively long duration might have allowed early parts of the course to have a buffering effect by providing less experienced students with skills already possessed by their more experienced colleagues [7]. The direct effects of experience might be greater for introductory courses which are typically of short duration.

To conclude, the present theoretical approach has resulted in many important insights. Paying greater attention to theory can help us to be more selective in the variables we use in our attempts to predict computing performance and to understand mechanisms underlying predictivity. For example, it appears that a major construct responsible for much of the present model's predictive power is intrinsic motivation. Future research might compare the predictive utility of a psychometric measure of intrinsic motivation (tapping both general intellectual and computing-specific factors) with the utility of more commonly used predictors. The present evidence suggests that such a measure might be valuable, particularly in educational counseling situations where there is no incentive for a student to give misleading answers. On the theme of gender differences, female computer engagement was just as positive as that of males, but females were less likely to own a computer and had less computing experience. While this did not hinder the present females' course performance, encouraging greater female computer ownership and experience should lead to greater female participation in technical computing courses, whether programming or applications-oriented.

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Table 1 – Observed correlation matrix (Pearson's *r*) for the eight variables in the theoretical path model.

	Gender	Ext	T-Poise	Intell	Engage	Own	Exp
Ext	-.07						
T-Poise	.27**	.14					
Intell	.31**	-.32**	.26**				
Engage	.16	-.04	-.03	-.03			
Own	.37***	-.10	.28**	.26**	.23*		
Exp	.29**	-.04	.10	.20*	.31**	.40***	
Perf	.14	-.22*	-.03	.42***	.24*	.05	.21*

*p<.05, **p<0.01, ***p<.0005 (df =84, one-tailed)

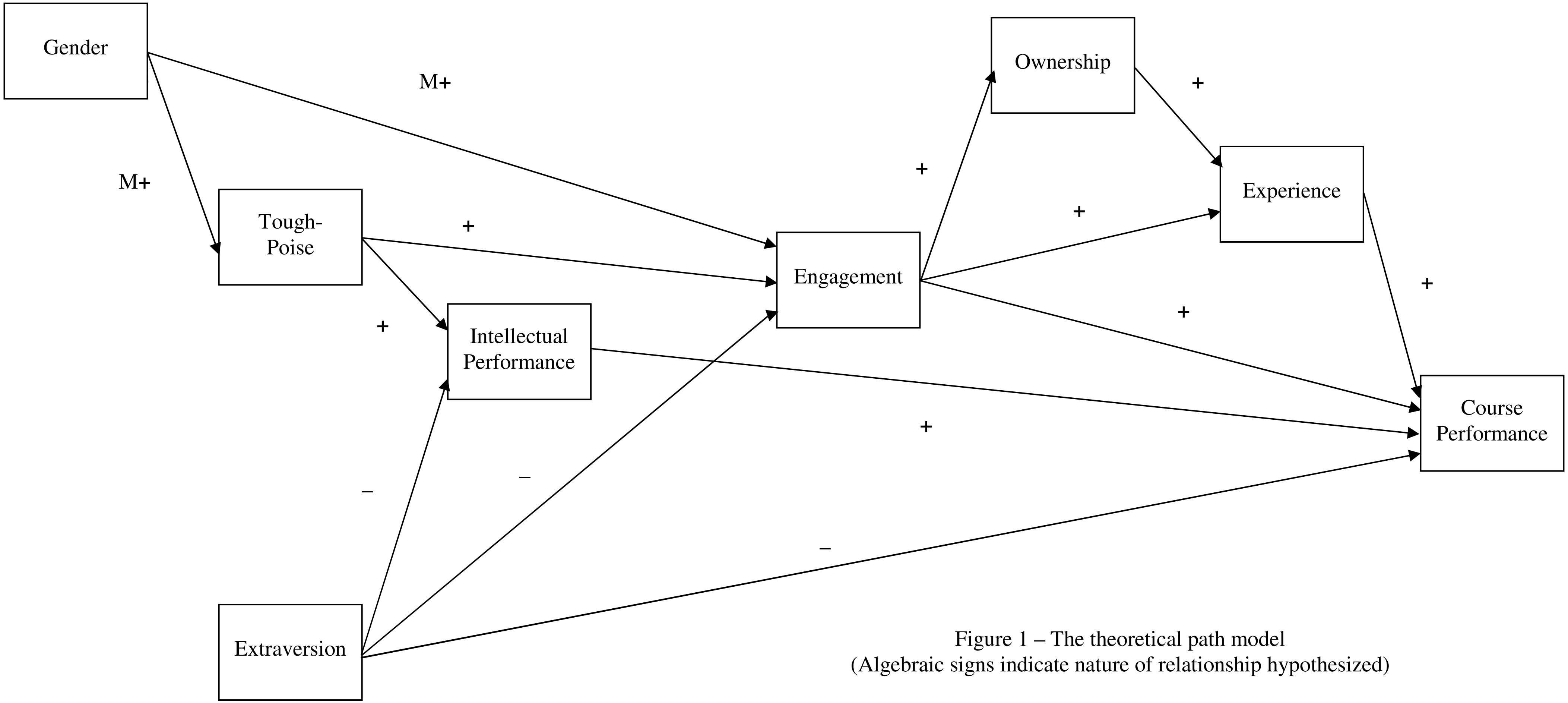

Figure 1 – The theoretical path model
(Algebraic signs indicate nature of relationship hypothesized)

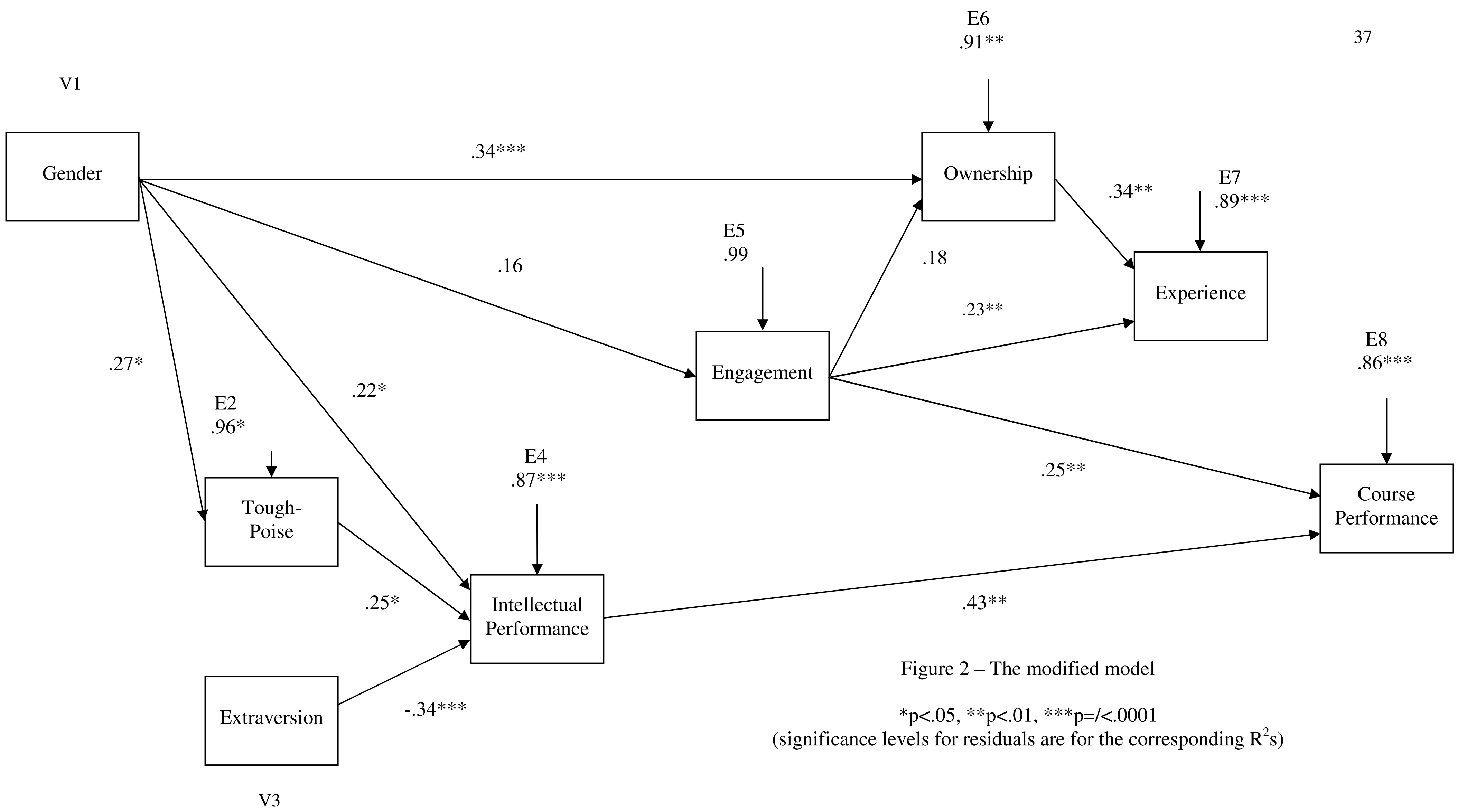

Figure 2 – The modified model

*p<.05, **p<.01, ***p=/<.0001
(significance levels for residuals are for the corresponding R^2s)